



Estimation of Cognitive Load of a Pilot Under Time and Task Pressure

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Abstract

Background: The growing integration of manned and unmanned aerial vehicles (MAVs and UAVs) in modern high-tech warfare demands a thorough understanding of pilot cognitive performance. Current battlefield decision-making models treat pilots as infallible operators, neglecting the impact of complex operational environments on their cognitive decision-making abilities, leading to a gap between computational outcomes and real combat scenarios.

Methods: This study proposes a multi-modal pilot cognitive decision-making model grounded in information theory. An interference characteristic matrix was constructed to quantify the influence of cooperative combat characteristics (UAV count, flight tasks, communication link quality), battlefield environmental factors (visibility level, task urgency), cockpit human-machine interface efficiency, and pilot personal capabilities on cognitive performance. A semi-physical simulation experiment was conducted with 27 participants using a Boeing 777-300 cockpit simulator equipped with an SMI iView X HED helmet-mounted eye-tracker. A within-subject repeated-measures design encompassed 54 task conditions across varying visibility levels (CAVOK, low visibility, night navigation), UAV counts (1, 2, 3), communication link quality (good, poor), and flight tasks (landing, climbing, level flight). Dependent variables included visual entropy (composite eye-tracking indicator), reaction time (RT), accuracy (ACC), and subjective cognitive load assessed via NASA-TLX and 3D-SART scales.

Results: Statistical analysis confirmed significant effects of all independent variables on cognitive performance. Cognitive decision-making levels decreased with increasing UAV count, reflecting heightened information load. Night navigation conditions yielded higher cognitive decision-making levels due to increased display contrast. Good communication link quality facilitated higher cognitive performance. Landing tasks imposed lower cognitive decision-making levels than climbing or level flight. The proposed multimodal model demonstrated strong correlation with empirical results across all 54 task conditions, outperforming the classical single-indicator 3D-SART method.

Conclusions: The interference characteristic matrix successfully quantifies the influential factors of pilot cognition and decision-making in MAV/UAV cooperative engagements. The multimodal model, integrating visual entropy, performance metrics, and subjective cognitive load, provides a comprehensive and accurate characterization of pilot cognitive decision-making ability. These findings offer significant practical implications for cockpit human-machine interface (HMI) design, pilot combat training optimization, and aviation safety improvement.

Keywords: Manned Aerial Vehicles (MAV); Unmanned Aerial Vehicles (UAV); Pilot Cognitive Load; Visual Entropy; Eye-Tracking; Multimodal Decision Model; Cooperative Combat; Information Theory

Introduction

The aviation industry is continuously evolving, with advancements in technology and changes in operational procedures necessitating a deep understanding of human factors, particularly the cognitive demands placed on pilots during critical situations. As aircraft designs become more complex and operational environments more dynamic, assessing and managing cognitive load experienced by pilots—especially under time and task pressure—is imperative for ensuring aviation safety and operational effectiveness.

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Received Date: 08 May 2026

Accepted Date: 11 Jun 2026

Published Date: 12 Jun 2026

Citation:

Kalam FA, Sultan M, Zhenbao L. Estimation of Cognitive Load of a Pilot Under Time and Task Pressure. *WebLog J Comp Sci Technol.* wjst.2026.f1203. <https://doi.org/10.5281/zenodo.20963341>

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Cognitive load, defined as the mental effort required to process information and perform tasks, plays a crucial role in aviation safety and performance. High cognitive load can impair decision-making, attentional focus, and situational awareness, leading to errors and potentially catastrophic consequences. In the context of modern high-tech warfare, the collaboration between manned aerial vehicles (MAVs) and unmanned aerial vehicles (UAVs) introduces new and complex cognitive demands on pilots, who serve as airborne commanders coordinating multiple systems simultaneously.

Existing battlefield decision-making models largely treat pilots as 'perfect operators,' ignoring or underestimating the variability in cognitive decision-making ability in complex combat environments. This oversight creates a gap between model-predicted outcomes and actual combat performance, reducing the accuracy of operational effectiveness assessments and commanders' decision-making processes. Addressing this gap is the central motivation of this research.

This thesis investigates the cognitive load and decision-making performance of pilots operating in MAV/UAV cooperative combat environments using advanced eye-tracking technology and multimodal measurement methods. The research proposes a multimodal cognitive decision model incorporating an interference characteristic matrix as input, aiming to quantify and model the influential factors on pilot cognitive performance. The findings contribute to cockpit HMI design, pilot training programs, and the broader field of aviation human factors.

Literature Review

Estimation of cognitive load in pilots can be achieved through several approaches. EEG combined with machine learning techniques has been used to evaluate cognitive workload in a subject-independent manner [1]. Ocular parameters including pupil diameter, fixation rate, and gaze distribution, alongside EEG signals, have enabled real-time cognitive load estimation during flight simulations [2,3]. Live-flight EEG data with feature selection algorithms provides further cognitive workload state indicators [4].

Quantitative cognitive modeling research has progressed significantly since the 1980s. Models such as SOAR (State Operator Act and Result), GOMS (Goals, Operators, Methods, Selection Rules), EPIC (Executive Process Interactive Control), and ACT-R (Adaptive Control of Thought-Rational) each offer frameworks for simulating human cognitive processes [9–24]. Decision-making models for pilots include structured approaches such as DECIDE, FOR-DEC, and DESIDE, as well as descriptive models such as the SHOR, RPD, PCM, and RAWFS frameworks [25–45]. However, these models generally do not quantify pilot-specific cognitive variability in dynamic cooperative combat environments.

Visual entropy, as a composite eye-tracking indicator integrating fixation, saccade, and blink parameters, has emerged as a promising physiological measure of cognitive load [60]. The NASA-TLX and 3D-SART scales provide validated subjective assessment tools [62,63]. The combination of objective physiological and subjective self-report measures enables a comprehensive multimodal characterization of cognitive state, addressing the limitations of single-indicator approaches.

Aims and Objectives

Research Aim: To develop and validate a multimodal cognitive

decision model for pilots operating in manned/unmanned cooperative combat environments, quantifying the impact of environmental and individual factors on pilot cognitive decision-making ability.

Specific Objectives:

- (1) Analyze interference factors (cooperative combat characteristics, battlefield environment, cockpit HMI efficiency, pilot capabilities) in manned/unmanned cooperative environments.
- (2) Establish an interference characteristic matrix using information theory principles to quantify these factors.
- (3) Develop a multimodal cognitive decision model integrating visual entropy, task performance, and subjective cognitive load indicators.
- (4) Validate the model through semi-physical simulation experiments under varying operational conditions.

Theoretical Framework

Information Theory Foundation

Information theory, pioneered by Claude Shannon in the 1940s, provides the mathematical foundation for this research. Shannon's entropy formula quantifies the average uncertainty of an information source, allowing systematic modeling of cognitive information processing. Key constructs employed include information entropy $H(X)$, conditional entropy $H(X|Y)$, joint entropy $H(X,Y)$, and average mutual information $I(X;Y)$ [46].

In the context of MAV/UAV cooperative combat, the pilot's cognitive decision-making process is modeled as a continuous cycle of information acquisition from the human-machine interface, analysis, and processing. External interference in the operational environment is analogous to noise in Shannon's channel model, reducing effective information transmission and increasing cognitive load.

Visual Entropy

Visual entropy serves as a comprehensive physiological indicator, synthesizing fixation duration, saccade speed, and blink rate into a single metric reflecting the pilot's cognitive state during information retrieval from the cockpit display. Higher visual entropy indicates more systematic and efficient information search patterns, while lower entropy reflects degraded cognitive processing under high workload conditions.

Visual entropy is calculated by identifying information blocks in the cockpit display, determining the probability and information quantity of fixation targets within each block, and applying Shannon's entropy formula to produce a composite indicator that quantifies the pilot's dynamic visual processing behavior.

Cognitive Load Theory

Cognitive Load Theory (CLT), proposed by Sweller, posits that both cognitive and working memory capacities are limited [52]. In the pilot's comprehensive information encoding process, cognitive load manifests hierarchically: task load (from time/psychological pressure and information load), design load (from interface color, layout, and graphic features), information selection load (from sensory to working memory), awareness load, discrimination load, understanding load, acquisition load, and prediction load.

Cognitive load is measured in this research through three complementary approaches: objective performance metrics (RT and

ACC), physiological parameter measurement (eye-tracking), and subjective assessment via NASA-TLX and 3D-SART scales.

Multimodal Cognitive Decision Model

The multimodal cognitive decision model (Equation 1) characterizes pilot cognitive decision-making ability (I) as a weighted function of the interference characteristic matrix (E), visual entropy (P), reaction time (T), accuracy (A), and subjective cognitive load (S):

$$I = f(E, P, T, A, S; w_1, w_2, w_3, w_4)$$

Equation (1): Multimodal Cognitive Decision Model.

Where w_1, w_2, w_3, w_4 are the relative weights of each indicator, determined empirically. This model moves beyond single-indicator approaches (such as 3D-SART) to provide a comprehensive characterization of pilot cognitive ability across multiple dimensions.

Methods

The experimental design employed a within-subject repeated-measures approach across a semi-physical flight simulator platform. All experimental procedures were conducted at the Human-Machine and Environment Research Group, Northwestern Polytechnical University (Table 1).

Interference Characteristic Matrix

The interference characteristic matrix was established through a three-round Delphi expert consultation process involving aviation and cognitive load domain experts. Factors were evaluated and weighted across four dimensions: (1) Cooperative combat characteristics (UAV count, flight task type, manned/unmanned cooperative hierarchy, communication link quality); (2) Battlefield environmental characteristics (task accuracy requirements, time urgency, visibility level); (3) Cockpit HMI efficiency (operational accessibility, operational visibility); (4) Pilot personal capabilities (flight experience, emergency event handling ability).

Reliability analysis (Cronbach's alpha) and factor analysis (communalities and contribution rates) were applied to the Delphi consultation data to validate the interference factor weightings and their relative contributions to pilot cognitive decision-making in the MAV/UAV cooperative environment.

Data Collection and Processing

Areas of Interest (AOIs) were defined within the Boeing 777-300 cockpit display interface, encompassing powerplant information, major system information, warning messages, and flight/navigation information panels. Eye-tracking data were processed to compute fixation duration, first fixation duration, total fixation duration per AOI, average blink frequency, fixation rate, scan path length, saccade frequency, saccade speed, and pupil diameter metrics.

Statistical analyses included Shapiro-Wilk normality testing, repeated-measures ANOVA with within-subject factors for all independent variables, post-hoc pairwise comparisons (Bonferroni correction), and Pearson correlation analysis to validate the multimodal cognitive decision model.

Research Contributions

This research makes four primary scientific contributions to the fields of aviation human factors and cognitive engineering:

See Table 2.

Key Findings and Results

The following table summarizes the principal experimental findings across all independent variable conditions:

See Table 3.

The comprehensive evaluation results indicate that the theoretical cognitive decision-making ability trends calculated from the predictive model across all 54 tasks demonstrate strong correlation with the empirical results from actual pilot operations. The multimodal model comprehensively characterizes pilot cognitive decision-making ability from cognitive load, visual entropy, and task performance dimensions—outperforming the 3D-SART single-indicator approach.

Conclusions

Summary

This dissertation has introduced a comprehensive, information-theory-based multi-modal cognitive decision model for pilots operating in MAV/UAV cooperative combat environments. The interference characteristic matrix successfully quantifies the influence

Table 1: Experimental Design Summary.

Participants	27 trained participants (aircraft design & human-machine engineering students)
Platform	Semi-physical flight simulator (Boeing 777-300 HMI) + SMI iView X HED helmet-mounted eye-tracker
Scenario	MAV/UAV cooperative combat; simulated engine fire alarm response tasks
Independent Variables	Visibility level (CAVOK / Low / Night); UAV count (1, 2, 3); Communication link quality (Good / Poor); Flight task (Landing / Climbing / Level flight)
Dependent Variables	Visual entropy; Reaction time (RT); Accuracy (ACC); NASA-TLX subjective cognitive load; 3D-SART situational awareness
Design	Within-subject repeated-measures design; 54 task conditions
Statistical Analysis	Normality testing; Repeated-measures ANOVA; Post-hoc pairwise comparisons; Pearson correlation analysis

Table 2:

#	Contribution	Description
1	Information Theory-Based Cognitive Decision Modeling	Proposes a cognitive decision modeling method based on information theory, analyzing pilot cognitive decision-making across information input, processing, and output perspectives in cooperative combat environments.
2	Interference Characteristic Matrix	Establishes a quantified matrix for factors (UAV number, flight tasks, visibility, communication link quality, cockpit HMI efficiency, pilot experience) influencing pilot cognitive decision-making.
3	Multi-Modal Cognitive Decision Model	Develops a validated multimodal model integrating visual entropy (eye-tracking), task performance (RT, ACC), and subjective cognitive load (NASA-TLX, 3D-SART) to characterize pilot cognitive ability.
4	Experimental Validation	Conducts semi-physical simulation experiments with 27 participants across 54 tasks, statistically validating the model through ANOVA, post-hoc comparisons, and correlation analysis.

Table 3: Summary of Key Experimental Findings.

Finding	Description
UAV Count Effect	Pilot cognitive decision-making levels decreased as UAV count increased from 1→3, due to higher information load and increased cognitive workload when monitoring multiple systems simultaneously.
Visibility Impact	Night navigation (instrument flight) yielded relatively higher cognitive decision-making levels due to increased stimulus contrast on display interfaces, facilitating alert information processing.
Communication Quality	Good communication link quality was associated with higher pilot cognitive decision-making levels, enabling more efficient information transfer in MAV/UAV cooperative operations.
Flight Task Influence	Landing tasks resulted in lower cognitive decision-making levels compared to climbing and level flight, as landing requires simultaneous collection of diverse information in a compressed timeframe.
Model Correlation	The multimodal cognitive decision model showed strong correlation with empirical data across all 54 tasks, outperforming the classical 3D-SART single-indicator method.
Visual Entropy Validity	Eye-tracking parameters (fixation, saccade, blink) combined as visual entropy effectively represented pilot cognitive state, confirming physiological measurement as a reliable objective indicator.
Interference Matrix	The interference characteristic matrix successfully quantified the influence of cooperative combat factors, battlefield environment, cockpit HMI, and pilot capabilities on cognitive performance.

of cooperative combat, battlefield environment, cockpit HMI, and pilot capability factors on cognitive decision-making. Experimental validation with 27 participants across 54 task conditions confirmed the model's effectiveness and accuracy. Research findings hold significant practical implications for cockpit HMI design, pilot combat training, and flight safety improvement.

Limitations

The relatively narrow selection of experimenters (n=27) and Delphi experts, driven primarily by time constraints, may limit the generalizability of findings. The selected experts were, however, highly qualified in aviation and cognitive load research. Cross-validation with additional data sources and methodological triangulation were employed to mitigate this limitation.

Future Work

Future research directions include:

(1) Expansion of interference factors to include battlefield threats, manned aircraft vibration, and overload conditions.

(2) Extension of physiological metrics to include EEG and ECG for more comprehensive multimodal validation, with a broader participant pool and more realistic operational conditions.

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